PROCEEDINGS

55. IWK

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TECHNISCHE UNIVERSITÄT
ILMENAU

Impressum
Published by

Publisher: Rector of the Ilmenau University of Technology
Univ.-Prof. Dr. rer. nat. habil. Dr. h. c. Prof. h. c. Peter Scharff

Editor: Marketing Department (Phone: +49 3677 69-2520)
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Faculty of Computer Science and Automation
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Univ.-Prof. Dr.-Ing. habil. Jens Haueisen

Editorial Deadline: 20. August 2010

Implementation: Ilmenau University of Technology
Felix Böckelmann
Philipp Schmidt

USB-Flash-Version.

Publishing House: Verlag ISLE, Betriebsstätte des ISLE e.V.
Werner-von-Siemens-Str. 16
98693 Ilmenau

Production: CDA Datenträger Albrechts GmbH, 98529 Suhl/Albrechts

Order trough: Marketing Department (+49 3677 69-2520)
Andrea Schneider (conferences@tu-ilmenau.de)

ISBN: 978-3-938843-53-6 (USB-Flash Version)

Online-Version:

Publisher: Universitätsbibliothek Ilmenau
ilmedia
Postfach 10 05 65
98684 Ilmenau

Home / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=16739

MODEL PREDICTIVE CONTROL OF A LABORATORY HIGH TEMPERATURE RETORT FURNACE

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ABSTRACT

In this paper the Model Predictive Control (MPC) of a High Temperature Retort Furnace is presented. The identification of a nonlinear model of the furnace was performed by a Multilayer- Perceptron (MLP) with external dynamics. Due to the necessity of the implementation of the MPC- controller in a Programmable Logic Controller (PLC) the relatively strong nonlinearities of the furnace are not explicitly considered. By the application of an Anti- Windup strategy the explicit constraint handling was avoided. Furthermore, a MIMO- structure of the MPC- controller was bypassed. Generally and in comparison to a PI- control the MPC exhibits a higher robustness in relation to nonlinearities. By usage of a predefined reference trajectory a significantly reduced velocity error in comparison to a conventional control is achieved.

Index Terms – Nonlinear Identification, Predictive Control, High temperature retort furnace control

1. INTRODUCTION

The control of industrial furnace over a wide temperature range is a known problem. The concurrence of different forms of heat transmission causes relatively strong nonlinearities. For the purpose of saving investment costs the power electronics and the heaters are often undersized in view of the control; this fact leads to strong constraints of the controller outputs and generates further nonlinearities. In addition, the construction of the retort furnace exhibits a problem with respect to the control. The jacket heaters are placed outside of the retort. Because the temperature inside the retort must be controlled, the retort forms an additional dynamical order.

Primarily good tracking behaviour is required for the control of the retort furnace. The reference trajectory is predefined by technological boundary conditions. All preceding facts led to the assumption that the application of MPC yields to advantages.

Firstly the paper describes the construction and the properties of the retort furnace. Thereafter the identification of the furnace is explained, before the design and results of MPC are described in detail. The paper ends with a conclusion.

2. THE RETORT FURNACE

The furnace is a Laboratory High Temperature Retort Furnace, which was developed and built by the company MUT Advanced Heating GmbH Jena.

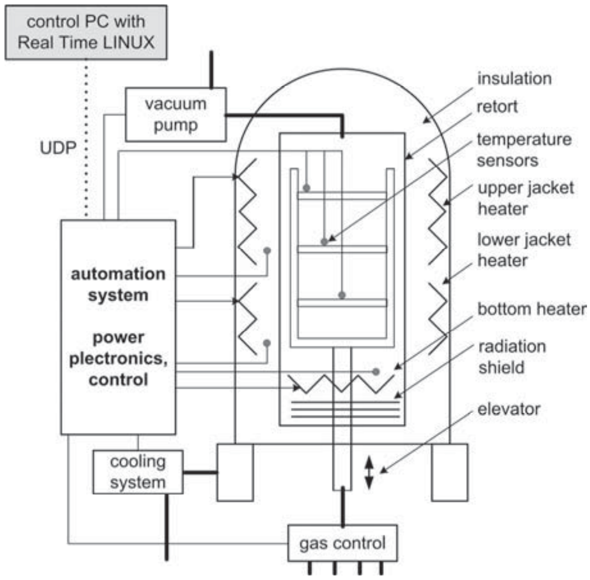

Figure 1: Construction of the retort furnace

Fig. 1 shows the furnace with the automation system. The construction consists basically of a retort, where the heat treatment is performed, a movable rack for the positioning of the material, jacket heaters, a bottom heater, a vacuum pump, a gas control unit and a water cooling system. The purpose of the furnace is the universal heat treatment of different materials. Types of processes are for instance sintering, debindering, glowing, tempering and soldering. In this paper the furnace is analyzed solely as a hot- wall furnace. That is, only the jacket heaters are used for supplying energy. The assembly is efficiently insulated to the environment. Temperatures up to 1200°C are adjustable in the retort with the option of different gas atmospheres (air, special gases, vacuum). The automation of the furnace is basically performed by a PLC SIMATIC S7 300. For the purpose of identification and prototypical application of MPC a Control- PC with a Real- Time LINUX environment was installed.

3. IDENTIFICATION OF THE RETORT FURNACE

The model of the retort furnace can be divided into two submodels:

- Model of the heater system (heater model). Inputs are the electrical powers of the jacket heaters; outputs are the measured heater temperatures.
- Model of the retort system (retort model). Inputs are the heater temperatures; outputs are the retort temperatures.

Each one of the two submodels possesses a 2x2-MIMO- structure. This structure requires a selection of two of the three temperature sensors inside the retort. By usage of physical knowledge the lower and the upper sensor is selected; this choice guarantees a high temperature homogeneity (see Fig. 1). For the identification and the control a sample time of $t_s = 40s$ is used.

3.1. Identification by means of the Multilayer-Perceptron (MLP)

The nonlinear properties of the statical and dynamical behaviour of the furnace become apparent by:

- Considerable gain variations of the heater system over the temperature range.
- Significantly violated superposition of the subsystems of the MIMO- structure of the heater system.
- Different time constants over the operating range. The time constants are smaller at low temperatures than at high temperatures.
- Different time constants for heating and cooling. The time constants are significantly smaller for the heating than for the cooling.
- The dynamic behaviour cannot be described sufficiently accurate by a linear differential equation even in a small operating range.

Fig. 2 shows the estimated static nonlinearity of the lower heater temperature (the dots represent the measurements). One recognizes the strong deviation in relation to the linear case.

In the beginning the identification was performed by a Wiener model for the heater system. However, it turned out that the model was not sufficiently accurate for the application, especially regarding the dynamical behavior. Therefore a more sophisticated approximation method was necessary. The artificial neural network (ANN) in the form of the Multilayer- Perceptron (MLP) with external dynamics offers the possibility of the universal approximation of nonlinear statical and dynamical behaviour and was proved in practice [2], [5]. In the following the structure and important properties of the MLP is briefly addressed. Subsequently the identification of the retort furnace with the MLP is described.

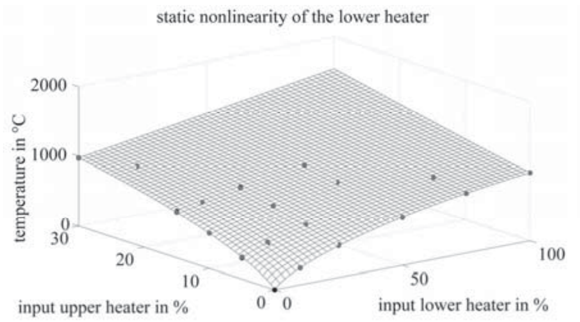

Figure 2: Static nonlinearity of the lower heater temperature

Without any extensions the MLP is a universal static estimator. With such an estimator one can get an approximation of the underlying process from measured data. The extension of the static MLP to dynamic problems is achieved with retarded samples [3], [4]. The mathematical description is performed by:

$$y(k+1) = h[y(k), \dots, y(k-n_y), u(k-d_\tau), \dots, u(k-d_\tau-n_u)]\,. \tag{1}$$

In (1) $h(\cdot)$ indicates the static nonlinear mapping of the MLP. The integers n_u and n_y denote the number of delayed samples (lags) of the input and the output of the system respectively. The number of the lags is fixed according to the estimated order of the process. Furthermore, a potential existing dead time d_τ must be considered. An adaptation of the estimator to a concrete problem can be divided into two subproblems:

1. Structure estimation.
    a. Estimation of the dynamical order and the dead time (structure of the external dynamics).
    b. Estimation of the complexity of the mapping (number of the adjustable parameters of the estimator).
2. Parameter estimation.

The structure estimation is performed by a- priori knowledge, special tests and/ or by direct search methods and is often not very systematic. The parameter estimation must be regarded as a nonlinear optimization problem, because the estimation error has a nonlinear relation to the parameters of the estimator. In principle, the problem can be solved by any nonlinear optimization method. As a suitable technique the Marquardt- Levenberg algorithm was proved [2], [5].

Concerning the external dynamics different structures can be used. The NARX- structure is the nonlinear counterpart of the linear ARX- structure and is used for the parameter estimation mainly. The usage of the MLP for simulation purposes is done in NOE- structure, which is the nonlinear counterpart of the OE- structure [2]. Special properties of the above configurations are not considered here; further information can be attained, e.g. in [2].

Following the procedure of the identification of the retort furnace with the MLP is explained. As described before, a division into two submodels namely the heater model and the retort model was performed. Both submodels possess MIMO- structure. The approximation was realized by decomposition of a MIMO- structure to n MISO- structures. Hereby n indicates the number of outputs of the MIMO- structure. For that reason the heater model and the retort model are represented by two MISO- structures respectively. Every MISO- structure is represented by one MLP estimator.

An important task while identification is the design of excitation signals [1]. For the identification of the furnace, excitation signals were designed, which fulfil the following criteria:

- Acceptable experimental effort (2-3 days),
- adequate excitation of the interesting power-density spectrum,
- sufficient exploration of the operating range.

For the design a maximally allowable heater temperature had been considered. For this reason the heaters were driven in closed loop and the excitation signals were designed for the reference trajectories of both control loops.

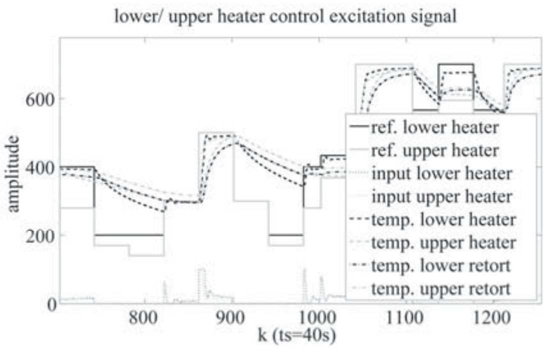

Figure 3: Excitation signals and measured data

Because of the negligible distortion no problem at the identification in closed loop has arisen. In order to keep the experimental effort small some application specific conditions were exploited. Firstly the reference trajectory is monotonically increasing at normal operation; secondly the heaters are driven in a defined ratio (see section 4). The hold time of the m- sequences was determined by means of a measured step response. The excitation signals have a duration of 44 hours. Fig. 3 depicts a detail of the excitation experiment and typical measurements of the heating powers, heater temperatures and retort temperatures.

The structure estimations of the models were performed by means of a- priori knowledge, experience and direct search. The results are summarized in Tab. 1.

	T lower heater	*T* upper heater
lags	3	4
neurons	4	3
	T lower retort	*T* upper retort
lags	1	1
neurons	4	4

Table 1: Structure of the MLP models

The number of the lags was fixed equal for all input values of a model. The parameter estimation was executed by means of the Marquardt- Levenberg algorithm; mainly NARX- structure and partly NOE- structure were used. The validation of the MLP models was realized with separate data.

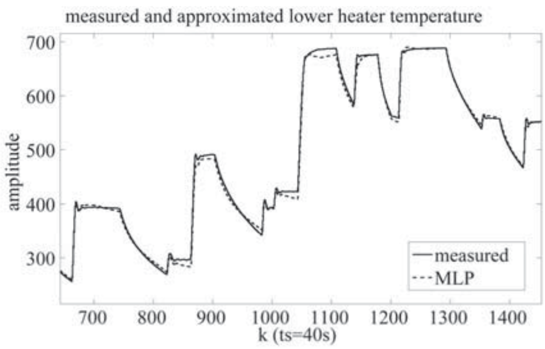

Figure 4: Identification results of the lower heater temperature model

Fig. 4 shows a representative result of the validation of the MLP models using the example of lower heater temperature. The heater system exhibits significantly stronger nonlinearities than the retort system. This fact is reflected in the identification results. In summary, the accuracy of the MLP models is assessed appropriate and useable in practice.

4. PREDICTIVE CONTROL OF THE RETORT FURNACE

Essential facts, which led to the decision of using MPC, were:

- A desired higher robustness of predictive control with regard to nonlinearities and load changes,
- improved tracking behaviour (no significant overshooting, reduced velocity error),
- an energy saving effect caused by reduced activity of the manipulated variables and the improved tracking behaviour.

The previously listed improvements relate to a conventional PI- control, which is the default solution. Subsequently, the principle of predictive control is described briefly. After this the application at the retort furnace is explained.

An essential note of model predictive control (MPC) is the utilization of a process model. With the help of the model the future course of controlled variables can be predicted. Thus one can determine the future error signal and the impact of future changes of manipulated variables. MPC belongs to the class of optimum strategies. In every sample an objective function, which is composed of a portion of the future error signal and a penalty term of the manipulated variable, is minimized explicitly or implicitly.

$$V(k)=\sum_{i=N_1}^{N_2}\left\| w(k+i\,|\,k)-\hat{y}(k+i\,|\,k)\right\|^{2}_{Q_i} + \sum_{i=0}^{N_u-1}\left\|\Delta\hat{u}(k+i\,|\,k)\right\|^{2}_{R_i} \tag{2}$$

The first additive term of the objective function (2) refers to the future error signal. The second term references the penalized changes of the manipulated variable. Here N_1 and N_2 indicate the prediction horizon, $\hat{y}(k+i\,|\,k)$ indicates the model free response, $w(k+i\,|\,k)$ is the setpoint, N_u the control horizon and $\Delta\hat{u}(k+i\,|\,k)$ the alteration of the manipulated variable. The summands represent weighted quadratic sums. The weighting is achieved with the matrices $\underline{Q}$ and $\underline{R}$. The functional (2) is minimized in every sample, if necessary with considering constraints. The parameters of the optimization are the alterations of the manipulated variable $\Delta\hat{u}(k+i\,|\,k)$ over the control horizon N_u. Characteristic for predictive control is the principle of receding horizon. Thereby the system is provided only with the first sample of calculated manipulated variable. After this the prediction and control horizon is moved one sample in the future and the described procedure is repeated [6].

So far the described principle of predictive control is valid for the linear and the nonlinear case. A nonlinear optimization problem must be solved, however, if the underlying process and the model are nonlinear. Nonlinear optimization (considering constraints) is a hard problem, especially with respect to real time [6], [8].

For the control the retort furnace is a nonlinear system with input and state constraints. However, the existence of constrains requires an iterative solution of the optimization problem in the linear case already.

Bearing in mind the previous facts and the restriction of implementation (PLC) essential simplifications were accepted in order to utilize a MPC at the retort furnace:

- Usage of a linear predictive controller,
- SISO- structure of the predictive controller,
- no explicit constraint handling.

The design of the control with respect to the foregoing restrictions is demonstrated below. The measurement of the heater temperatures offers the introduction of additional control variables, so that the cascade principle is beneficially employable. The predictive controller should be used obviously as the master controller, since only the master controller enables the exploitation of a predefined reference trajectory. Moreover the role of the master controller is decisive in view of the overall control performance. Because of the restrictions SISO- structure and linearity of the controller a single virtual control variable is calculated based on both measured retort temperatures according to (3).

$$T_R=\frac{T_{Ro}+T_{Ru}}{2} \tag{3}$$

The emerging control variable guarantees an optimal temperature distribution inside the retort. The setpoint is not regarded, because it is in any case equal for both retort temperatures.

By identification it is known that the heater system contains the strongest nonlinearities of the overall process. It is further known that the nonlinearities are mainly of static nature. The slave control loops linearize the heater system implicitly with respect to the static behaviour. The linearization, however, is bounded by the constraints of the manipulated variables. Since the predictive controller is used as the master controller, it is disburdened mainly with respect to nonlinearities (see Fig. 5).

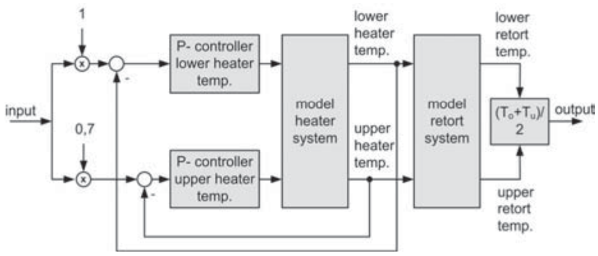

Figure 5: Structure of the process controlled by MPC

The lower and the upper heater temperature have different static gains concerning the retort temperatures. Therefore the setpoints of the slave controllers must be adapted (usage of time invariant factors). The controllers by themselves are of proportional type, because position errors are meaningless. Furthermore the dynamical order of the substitution process (see Fig. 5) controlled by the predictive controller is kept low and the parameterization effort remains small. Due to the constraints of the heater controllers (especially the unavailable cooling), a decoupling of the heater system was not taken into account.

The operation of the predictive controller depends substantially on an internal model. Considering the cascade structure the internal model is represented by the entire arrangement of Fig. 5. For the reasons of applicability and simplicity the arrangement of Fig. 5 was approximated by a linear low- order ARX- model. For this purpose the model arrangement was excited by a suitable m- sequence.

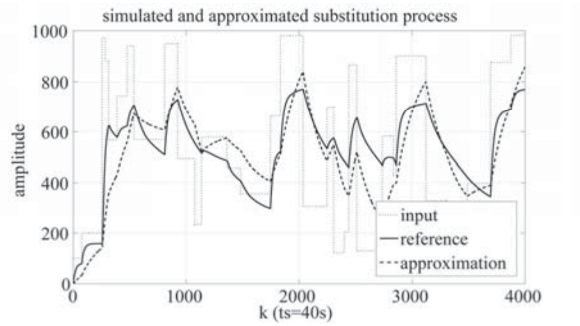

Figure 6: Approximation of the substitution process for the predictive controller

Fig. 6 shows the result of the approximation. The estimated ARX- model has first order and is described by the following difference equation:

$$y(k) = 0{,}00581\ u(k-1) + 0{,}99432\ y(k-1) \quad . \qquad (4)$$

The approximation error could not be reduced by utilization of a higher dynamical order. The gained internal model shows partly considerable errors, which are caused by nonlinearities, couplings and constraints of the approximated model arrangement.

A further task was the choice of a suitable MPC algorithm. For various reasons the GPC (Generalized Predictive Control) algorithm was selected. GPC determines the prediction by means of difference equations. In order to achieve integrating behavior, the ARX- model is expanded to the CARIMA- model [7]:

$$y(k) = \frac{B(q^{-1})}{A(q^{-1})} q^{-d} u(k) + \frac{C(q^{-1})}{A(q^{-1})} \frac{e(k)}{\Delta} \quad . \qquad (5)$$

The prediction composed of the free and the forced response is expressed as follows:

$$\underset{\rightarrow}{\hat{y}} = \underline{G} \Delta \underset{\rightarrow}{u} + \underline{F}\, \underset{\leftarrow}{y} + \underline{G}^* \Delta \underset{\leftarrow}{u} \quad . \qquad (6)$$

The matrices $\underline{G}, \underline{F}, \underline{G}^*$ are determined using the coefficients of the CARIMA- model (5). The calculation is performed by means of the Diophantine equations or Matrix methods. Using (6) and neglecting the right hand side term with future inputs, the free response is determined in every sample. The solution of the optimization in the unconstrained case is [7]:

$$\Delta \underset{\rightarrow}{u} = (\underline{G}^T \underline{Q} \underline{G} + \underline{R})^{-1} \underline{G}^T \underline{Q} \, (\underset{\rightarrow}{w} - \underset{\rightarrow}{\hat{y}}) \quad . \qquad (7)$$

An essential issue of the furnace control with MPC was the neglect of explicit constraint handling. The solution used is the utilization of an Anti- Windup strategy. In comparison with explicit constraint handling, the usage of an Anti- Windup strategy normally causes a suboptimal solution of the optimization problem, but it has the important advantage of a significantly lower computational burden. A predictive controller possesses no explicit integrator. However, fundamental for the controller is the internal model, which is supported by an incorrect manipulated variable in the case of an active input constraint. Hence the prediction becomes incorrect, even if the internal model is perfect. As a result effects similar to the usage of controllers with explicit integrators occur. The solution is the detection of an active input constraint; the constrained (clipped) manipulated variable is then used for the computation of the prediction by the internal model. The foregoing method is simple but very powerful. The disadvantage is the loss of optimality in the case of control horizons $N_u > 1$. Because of the cascade structure the constraints of the slave controllers are processed additionally.

Slave controller lower heater	$K_P = 2$
Slave controller upper heater	$K_P = 0{,}8$
Master controller (MPC)	
prediction horizon	$N_1 = 1$, $N_2 = 10$
control horizon	$N_u = 1$
error signal weighting	$\underline{Q} = \underline{I}$
input activity weighting	$\underline{R} = 0{,}4\ \underline{I}$
set point trajectory	predetermined

Table 2: Controller settings

Below the results of predictive control of the retort furnace are presented. Because of the complexity of the process (nonlinearities etc.) the adjustment of the controllers by systematic calculations is impossible. The controller settings (see Tab. 2) were found by means of qualitative comprehension of the impact of controller parameters and with the help of simulations (MLP model).

Fig. 7 and Fig. 8 depict the result of predictive control of the retort furnace with respect to the conditions normal air and small load. The reference trajectory possesses three plateaus (300°C, 600°C, 1000°C) and ramps with a slope of 600°C/h. The tracking and the stationary behaviour are assessed well. Furthermore nearly perfect aperiodic transient behaviour is denoted over the whole temperature range. Also the homogeneity is assessed well. Tab. 3 shows a comparative presentation of the results of MPC and PI- control of the retort furnace. Both controllers are master controllers. It is obvious that the predictive controller exhibits advantageous dynamical behaviour. This fact is especially apparent with respect to the velocity error. Due to the ability of using a predefined reference trajectory the predictive controller gains significantly improved results. At the assessment of the above results it must be mentioned that the PI- control exhibits undesired strong aperiodic behaviour at the transition to the plateaus of 600°C and 1000°C. For example, the control deviation at sample $k = 350$ still amounts to 15°C. The control variable of MPC is nearly stationary at this time already.

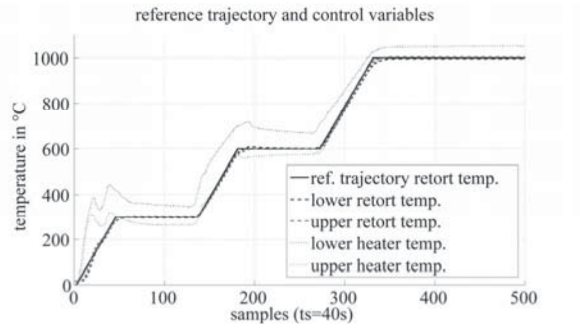

Figure 7: Result of predictive control of the retort furnace (control variables)

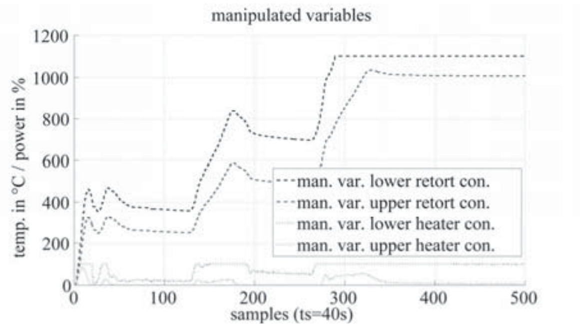

Figure 8: Result of predictive control of the retort furnace (manipulated variables)

	PI	MPC
overshoot	< 12°C	< 8°C
position error	< 1°C	< 1°C
velocity error	< 55°C	< 25°C
homogenity	< 11°C	< 11°C

Table 3: Comparison of PI- control and MPC- control

5. CONCLUSION

In this paper the Model Predictive Control (MPC) of a High Temperature Retort Furnace is presented. The identification was performed by means of a Multilayer- Perceptron (MLP) with external dynamics. The development of the control strategy was mainly influenced by the necessity of the implementation in a Programmable Logic Controller (PLC). This restriction entails the need of essential simplifications, especially a linear predictive controller without explicit constraint handling. The control structure is a cascade in which the predictive controller is employed as the master controller. The linearization of the furnace is performed by means of the slave control loops and the estimation of an internal model with linear structure. Explicit constraint handling of MPC is bypassed by the utilization of an Anti- Windup strategy. Furthermore, a substitution process with SISO- structure was built, and as a consequence, also the MPC has SISO- structure. The design of the control strategy and the controller adjustments were basically performed by means of the nonlinear MLP model.

As a result a quite good performance of the control is achieved despite of the strong nonlinearities of the furnace and the extensive simplifications of the design. In comparison with a usual PI- controller the MPC attains a higher robustness with respect to nonlinearities. The utilization of a predefined reference trajectory by the predictive controller results in a considerable reduction of the velocity error.

ACKNOWLEDGEMENT

This work was supported by the AiF (Arbeitsgemeinschaft industrieller Forschungs-vereinigungen "Otto von Guericke" e.V.).

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